The role of machine vision in industry 4.0: A textile manufacturing perspective

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Abstract— **As we move forward to the fourth industrial revolution, findings in the state-of-the-art enhance the technological advancements in the research community as well as the business one, in particular the textile manufacturing, being here reviewed. In industry 4.0, the silos-free integrated systems sense the entire manufacturing environment by using sensor- and vision-based systems while enable multicorrelation zero-faults results with the minimum required data. Furthermore, the role of computer vision is vital in the deployment of cyber-physical systems, as the rich textural information provided by images through the scene's appearance, can be translated into various findings. The paper at hand examines the existing appearance-based techniques in textile manufacturing over the previous five years. Moreover, open challenges and research gaps are highlighted. Through our analysis, we show that high performances are achieved mainly when vision-based systems are employed. Opportunities regarding one-batch fabric production without the need to promote multi-level integration are also proposed. Lastly, our findings exhibit that the self-adaptable visual features in textile manufacturing can be integrated with existing systems, e.g., cyber-physical ones, to observe the fabric factory in real-time while defects are corrected without scraps creation.**

I. Introduction

Textile manufacturing, also known as "the cottage industry", historically was the first one created. During the first industrial revolution, water and steam-powered loom mechanical machines permitted mass production. Through the years, textile manufacturing underpinned regional economic growths and country relationships across suppliers, producers, and consumers [1]. Nowadays, consumers give more attention to the quality and the unique characteristics of the products while their daily habits are continuously changing due to the technological advancements. At the same time, the worldwide manufacturing model moves forward to customized production, overcoming the traditional mass production process. To this end, textile producers should adapt their mindset and modernize their industry by transforming their methods and equipment, aiming to follow the rapid changes. A challenging factory is characterized by self-capable network infrastructures, autonomous systems, and integrated management techniques with advanced processing methodologies that enable zero-defect manufacturing [2].

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Autonomous systems with self-adaptable capabilities are enabled by the well-known industry 4.0 concept. The German initiative regarding industry 4.0 has firstly introduced at the Hanover Fair, wherein the government tried to strengthen the native industrialists among the worldwide market leaders. Similarly, various initiatives followed this direction by digitizing their factories as well as the overall supply chain leading manufacturing into the fourth industrial revolution era [3]. Besides, this revolution has also affected other disciplines, such as civil infrastructure, shipyards, and agriculture [4], [5].

Considering that businesses hesitate to adjust their mindset and welcome the new technologies, the academic infrastructure under the title "textile learning factory 4.0" is also established to provide real-time demonstration between lean production and industry 4.0 operations [6]. More specifically, the latter is based on the future factory, wherein cyber-physical production systems (CPPSs) are employed to interact via the cloud- and edge-based infrastructures, collect real-time information from visual and/or sensor assets, and analyze the information using advanced techniques that strengthen human-machine collaboration [7]. Furthermore, the advancements of artificial intelligence (AI) combined with the available processing power capabilities enhance the autonomous decision-making of the system in quality-related operations, production optimization, and failure assets predictions [8]. In general, the customized production of textile manufacturing requires technologies which massively gather data and provide crucial decisions, such as the ones machine learning techniques can offer [9], [10].

Machine vision consists of non-destructive techniques (NDTs) used in various industries to collect the characteristics and the morphology of an object without physical interventions. Its most common usage concerns quality-based applications, wherein the extracted visual features are highlighted and presented to the corresponding operators responsible for the final decision. Following the continuous progress in the AI techniques, the machine vision's functionalities are also improved via enabling self-adaptable decision features. Moreover, during the industry 4.0 era, machine vision systems are adopted in non-quality applications, viz. autonomous transportation systems, health and safety inspection systems, collaborative robots, and ecosystems. Nevertheless, in textile manufacturing, machine vision replaces human interventions throughout the production processes and enables fully customized fabrics based on the customer's needs.

As the fabric manufacturers need to facilitate the personalized manufacturing without defect challenges, computer vision techniques will be continuously integrated into the textile infrastructures strengthening the adoption of industry 4.0. Having that in mind, in this paper, we examine the machine vision applications that have been applied or tested in textile industries. Our main contributions are:

- A review analysis of vision-based systems used in textile manufacturing.
- A representative presentation of the existing contributions in textile-related machine vision applications.
- An informative conclusion regarding the maturity level of industry 4.0 systems based on machine vision, the open-challenges in the field, and the future opportunities.

This paper is structured as follows. In Section II, we present the methodology protocol followed for our review. Next, the analysis of the fabric production process and the computer vision techniques are discussed in Section III, while Section IV provides the results. Lastly, in Section V, we give our conclusions and the proposed future work.

II. Methodology

Accounting that the machine vision is considered a technology that can provide self-adaptable features in the cyber-physical systems' architecture and the competitive textile manufacturing environment, this manuscript aims to simplify the relations between fabric manufacturing and machine vision under the auspices of industry 4.0. Therefore, this review analysis is based on the answer of the following question: *"How does the textile production process benefit from machine vision technology in the context of industry 4.0?* The role of machine vision in the fourth industrial revolution and especially in textile manufacturing is achieved by creating a search query to collect the corresponding papers from academic libraries, viz. ACM Library, IEEE Explore, and Science Direct, from January 2016 to January 2021. The exploited search query was: `(``computer vision" OR ``machine vision" OR ``robotic vision" OR ``vision-based" OR ``appearance-based") AND (``cyber-physical" OR ``embedded system") AND (``industry" OR ``manufacturing" OR ``shop floor" OR ``production").`

A multitude of 2825 manuscripts was indicated. Next, a duplication check was performed and then the abstract and title of each paper were examined to select the ones that recount "machine vision." Almost half of the manuscripts were filtered out, while the chosen papers were clustered in industry-specific categories. Throughout the final stage of this survey, we examine 15 that were refereed in textile manufacturing. The other papers report systems and methods from clothing manufacture, such as contour, shaping, footwear industry, rug producers, recycling centers, or the textile or clothes industry.

III. Textile Industry

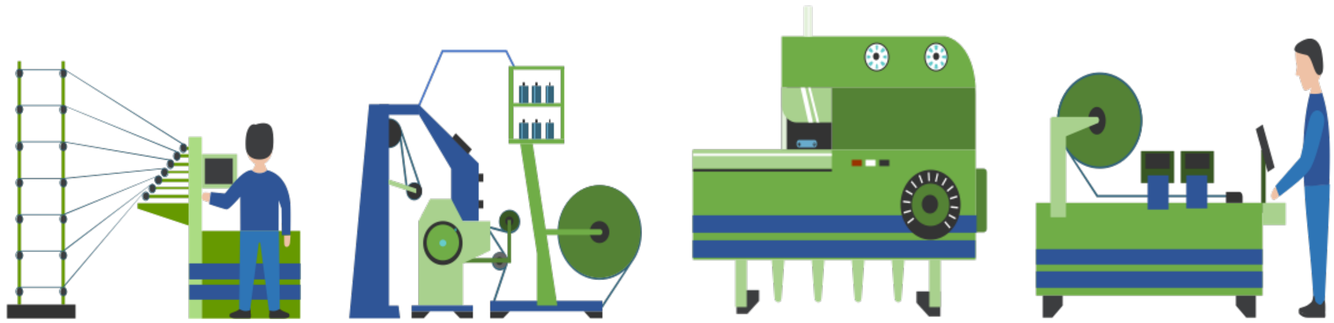
Textile manufacturing constitutes one of the most popular and oldest industries, which have been transformed through the revolution. Its production steps include the yarn tubes creation, the coloring procedures, the sewing and knitting processes, and the final quality control operations, which are executed before the distribution to the factories for further shaping. The following section describes the machine vision systems used for each production stage while their impact on textile manufacturing is highlighted.

A. Fabric factory

During the yarn production, a sequence of drawn and twisted actions that spin the fibers together to transform them into yarn is performed. The next stage is the weaving, where two sets of yarns stretched out in straight lines are intertwined to form fabrics. Subsequently, dyeing or additive processes occur. In particular, the fabric is given the dedicated color (adsorption and diffusion actions), or the second layer of sewing stamps is applied. Finally, unique technical characteristics such as flame retardance, water resistance, smoothing are given to the fabric using various chemicals. The phases mentioned above include quality control, positioning, and other functionalities based on machine vision systems that improve the textile factory's overall efficiency and upgrade the delivered products.

1) Yarn production: A series of processes convert the raw fibers into yarns that are further used to produce textiles at the yarn production. The bobbing process constitutes a vital step in the production, where the yarns are tightly wrapped in yarn tubes. Unfortunately, when the bobbins are transferred to the next stage, yarn residues remain in the head, middle, or tail of the yarn tubes, increasing the costs and reducing the production efficiency. Therefore, aiming to address this challenge, a vision-based detection system was developed to automatically indicate the residents in the bobbing machines and notify the system about the event. More specifically, the algorithm separates the image into RGB channels, next apply gradient-based feature extraction in the three channels, and finally compares the results against predefined thresholds to detect the residents. This system was tested in a real-scale bobbin pipeline, achieving a timing of 30ms and an error rate of 2% [11]. However, apart from the visual inspection of the bobbin machines, there are advancements in the yarns' quality check process. The machine vision technology is used to extract the yarn's characteristics and identify the defects such as thin or thick places and neps [12]. Li *et al.* propose a diameter image processing unit (DIPU) that continuously captures yarn images, analyzes the sequential sampling of their points, and finally measures the hairiness and defects using image subtraction techniques [13].

2) Weaving: It is well known that defect detection is difficult during production by experienced operators, but there are advancements in industrial knitting processes. Nevertheless, as hall or laddering defects are easily detectable by in-situ systems, operators still identify stripes after the production. Therefore, a method was developed to identify



(a) The yarn production stage (b) The weaving Stage (c) The dyeing and additive sewing stage (d) The finishing stage

Fig. 1: The textile manufacturing factory is segmented in four production stages.

the stripes in circularly knitted fabric to minimize the time retrieval between production and human-based stripe quality processes. The algorithm improves the quality of the image with Gabor and Matched filters, extracts visual features using different extraction techniques, e.g., local binary patterns (LBPs), histogram of oriented gradients (HOG), or gray level co-occurrence matrix (GLCM), and classifies the defects using a support vector machine (SVM) or random forests. It was shown that the extracted descriptors from LBM and GLCM perform better than HOG ones, highlighting how the visual features' choice affects the method's efficiency [14].

In weaving loom machines, a vision-based pipeline was developed to adjust the speed of the loom shaft reducing the defects of the fabrics. Its sub-system identified the variance of the fabric's density between two sequence points comparing the corresponding GLCM features. This way, a machine's speed adjustment was achieved [15]. Moreover, algorithms that categorize the most common fabric defects have also been proposed. non-complex algorithm was developed to detect tissue defects based on histogram equalization in gray-scaled images using cumulative distribution function (CDF), but this method cannot be applied in the manufacturing environment due to its low accuracy (90%) [16].

Automatic sewing machines are used in fabric factories to reduce costs. Unfortunately, one of the most common defects is the faulty lattice weave patterns, commonly occurred in the swing zone. To tackle this challenge, a vision-based framework was proposed to track individual fabric threads providing their position and orientation while discovering repetitive lattice faults. The detection of the blobs was achieved by the maximally stable extremal region (MSER) method, and description vectors were generated through the binary robust invariant scalable keypoints (BRISK) algorithm [17]. Compared with other systems, the vision-based ones achieve lower rotation tracking errors while operating in real-time [18].

Other advanced techniques were developed to tackle the diversity of the patterned fabrics. In particular, this challenge was mainly addressed using sequential detection of image defects. Additionally, the fabric frames were segmented into blocks thanks to the pattern's frequency. Finally, the defect position was indicated through feature dictionary construction techniques, i.e., GLCM and LBP, and feature matching, achieving better performance than other modern non-negative matrix factorization techniques, while the computational complexity was also reduced [19]. A different approach was proposed by Li *et al.*, which was based on biological vision modeling. The mechanism was simulated to represent fabric images with complex textures. The low-rank representation technique integrated with Laplacian regularization and dictionary learning provided a detailed saliency map wherein the defects were highlighted. The method's efficiency was improved using a linearized alternating direction technique with an adaptive penalty (LAD-MAP) to solve the constructed models enhancing the detection timing around 60% compared against the alternating direction method of multipliers (ADMM) [20].

Concerning deep learning approaches in the field and considering the limitation of available datasets due to the time-consuming and high-cost processes, an image-to-image translation framework was proposed that uses generative adversarial networks (GANs) to synthesize new defect in fabrics. Tests exhibited that the generated color-sensitive fabrics were more realistic using U-Net architecture than ResNet in model training [13].

3) Dyeing and additive processes: Traditionally, the third step of fabric manufacturing includes dyeing processes, i.e., where the desired color is given to the whole fabric. However, during the literature review, we observed no significant advancement in the specific procedure using a machine vision system. Therefore, instead of that, there are additive color and sewing stages that are further described. Moreover, due to the fabrics' distortion, the textile printing is a challenging procedure that leads to poor quality of products. To tackle this challenge, Ren *et al.* proposed a novel fine-grained digital printing system based on machine vision techniques to align the printing-head onto the non-planar fabrics in a continuous manner. Furthermore, the system analyzed the product's deformability by extracting visual features with a Gabor filter and generating a probability map with random forest classification. As the last step, a transformation matrix was calculated to correct the printing-head

Paper	Year	Category	Environment	Machine/Process	Prod. Stage	Decision	HI	AI	Int.
[14]	2016	Knitting Defect Detection	Laboratory	Circular Weft Knitted Fabrics	Weaving	Identify	no	no	no
[15]	2017	Loom Defect Detection	Laboratory	Weaving Loom Fabric	Weaving	Action	no	no	no
[21]	2017	Self-adaptable Correction	Industrial	Printing Machine	Dyeing	Action	no	yes	no
[18]	2018	Individual Blood Identification	Industrial	Sewing machines	Weaving	Identify	no	no	no
[20]	2018	Defect Detection	Laboratory	Weaving Loom Fabric	Weaving	Identify	no	yes	no
[16]	2019	Defect Detection	Laboratory	Weaving Loom Fabric	Weaving	Identify	no	no	no
[11]	2019	Resident Detection	Industrial	Boobing Machines	Yarn	Identify	no	no	no
[19]	2020	Defect Detection	Laboratory	Weaving Loom Fabric	Weaving	Identify	no	no	no
[22]	2020	Yarn Defect Detection	Laboratory	Boobing Machines	Yarn	Identify	no	no	no
[23]	2020	Self-adaptable Correction	Laboratory	CNC sewing mahcines	Dyeing	Action	no	no	no
[24]	2020	Characteristic Identification	Laboratory	Quality control	Finishing	Classify	yes	yes	no
[25]	2020	Edge Detection	Industrial	Quality control	Finishing	Identify	no	yes	yes
[26]	2020	Edge Detection	Industrial	Quality control	Finishing	Identify	no	no	no
[27]	2020	Characteristic Identification	Laboratory	Quality control	Finishing	Classify	yes	yes	no
[13]	2021	Defect Creation	Laboratory	Weaving Loom Fabric	Weaving	Create	no	yes	no

TABLE I: Demonstration of all the textile-related papers included in our review, presenting the problem category, the tested samples, as well as several method and system details. The acronyms HI, AI, and Int. are used for Human Intervention, Artificial Intelligence and Integration, respectively.

movements, achieving prints in an area of 0.12m^2 in less than 4 seconds into full-embroidery and lace fabrics [21]. Apart from the colored fabric needs, the market requires different embroidered seam patterns onto the fabrics. As in the above challenge, the computerized numerical control (CNC) sewing machines should be accurate during their actions despite the condition of the fabrics. A contemporary vision-based pipeline was proposed by Geller *et al.* that identified the seam patterns, then identified the stitch positions, and finally, the CNC sewing machine was automatically corrected. This way, the faulty distances between the planned and real additive actions were eliminated [23].

4) Finishing: Throughout the last step of textile manufacturing, fabrics are strengthened with unique characteristics via chemicals. As the fabric smoothness appearance is a crucial characteristic affecting the quality of the products, a multi-camera system was proposed that identifies the textureless fabrics [24]. More specifically, it was based on the structure-from-motion (SFM) and patch-based multi-view stereo (PMVS) techniques to reconstruct the fabric's surface, the model of bag-of-visual-features to extract the salient elements of the wrinkled fabric, and a k-nearest neighbor (k-NN) classifier to identify the fabric smoothness. This way, a recognition rate of 93.3% was achieved [24]. Besides, a more complex framework for the same classification problem was introduced in [27], wherein the smoothness assessment was based on a pre-processing algorithm, a convolutional neural network (CNN) architecture, and a label smoothing component. The proposed model was composed of five individual layers, viz. convolutional, max pooling, batch normalization, shortcuts, and rectified linear unit (ReLU) activation one, while a fully-connected was its last layer. As a result, the model extracted robust features for fabric smoothness requiring significantly less time than other CNN architectures, while achieving high accuracy, reaching a score of 95.38% under errors of 0.5 degrees [27].

After the chemical processes, the majority of the fabrics are damaged at the edges. An edge detection methodology based on Canny's algorithm combined with Huff's line detection pipeline was introduced [25] to reduce the faulty shipped textile products. It was proven that the vibration and noise did not affect the edge detection while the system could transmit data in real-time [25]. Researchers developed a system suitable for synthetic leather manufacturers using the Otsu and Sober edge detection methods to identify the abnormalities regarding the edge crimping defects. The system was tested for 30 dates and achieved a 95% accuracy score with rollers moving speed at 0.6m/s [26].

IV. Discussion

Our review analysis showed the indications that clarify how the machine vision technology adapts to the era of the fourth industrial revolution and its benefits in textile manufacturing. The evidences were further analyzed to the following three subsections, categorized in: current stage, trends and future directions.

A. Analysis

The textile industry is characterized by repetitive automated actions and quality-related applications that are the basis of mass production and reduced defects. From the raw-fibers sewing stage to fabric creation, the isolated production systems create data processed to offer valuable information to the operators or other centralized management systems. Machine vision systems are used to capture contextual images from the fabrics. The images' quality is improved with filters and advanced computer vision techniques, processed with intelligent, machine, and deep learning pipelines to finally provide information about the characteristics and quality of the fabrics. Furthermore, machine vision technology is also applied in frameworks to personalize the products and improve their quality.

Through the survey, we indicate the important points of the described applications and methods in Sec. III following a structured database as presented in Table I. The various categories of vision-based systems in textile manufacturing are grouped. Our structured database includes information about the applied application's "environment" (industrial or laboratory), the facing challenge "category," the involved "machine or process," and some other characteristics which represent the maturity level of the system's intelligence, including "artificial intelligence" appearance, "human intervention" (HI), "integration" with other vital systems among others. According to the review analysis, it is notable that vision-based research is mainly focused on the weaving (46,6%) and finishing (26,6%) production stages in contrast with the small adoption percentages of yarn (13,4%), as well as dyeing and additive (13,4%) processes.

B. Trends

We do not come across machine vision systems as part of the dyeing process, making sense as the dying quality control systems are explored in previous decades, eliminating the color defects. In contrast, the current trend includes systems that try to capture the deformability of the fabrics to be adapted to the movements of the second layer sewing CNC [21] or printing machines [23].

In the weaving manufacturing stage, where the yarns are transformed into fabrics, this study proves that the vision-based systems are used for defect detection in complex patterned fabrics [14], [16], [18] or individual threads [18] and self-adjustments action, such as speed adjustment of loom machines [15]. Apart from that, we believe that learned features should be further applied to the functions of the industrial sewing machines, reducing the quantities of fabric defects.

AI provides "thinking" capabilities in the machine vision systems to classify or predict situations that have not ever met before. As Table I presents, in the examined five years, it is clear that two out of five papers include AI capabilities, a notion that is indicated in the automotive manufacturing review [28]. However, from 2016 to 2018, 29% of them utilize AI techniques, while 50% of the reviewed papers use the machine- or deep-learning methodologies [24], [25], [26], [27], [13]. As the adoption of AI is significantly increased, researchers explore the following generation of training architectures, such as federated learning and edge-based learning. In contrast with the automotive manufacturing review analysis [28], this study proved that the textile manufacturers may not trust the intelligent machine vision system as the majority of the developed systems was tested in laboratory environment. From 2016 to 2018, around 40% of the papers were applied in the industrial environment. However, this rate was decreased to 25% in the following two years, as presented in Table I. The authors believe that this trend occurred due to the lack of understanding of how machine vision technology can improve the efficiency of production procedures under the umbrella of industry 4.0.

C. Future Direction

Machine vision is a technology that can be characterized as the "eyes" of industry 4.0 and can provide valuable insights about the status, the progress, and the defects of the fabrics, through the production in real-time. Based on the results presented in Table I, open challenges are identified and discussed in the following paragraphs. In addition, some of the analyzed solutions fulfill the "through-engineering solution" characteristic of industry 4.0, where innovative techniques from other industries are used in textile manufacturing. The biological visual-based method is a modern technique for complex and pattern fabrics that offers a new solution to the manufacture [20]. Although the solution has been only applied in a laboratory environment, it has to be tested in industrial infrastructures as well as in the weaving production procedures. In the finishing process, one of the examined systems, viz. fine-grained digital printing system, can be considered as an essential tool as it provides self-adaptable actions based on the fabric conditions enabling customization features that produce personalized fabrics [21]. Furthermore, the philosophy of self-controlled and self-adaptable functionalities should also be adapted in the other manufacturing stages such that machines shall modify their operating setting to put right the production or possibly self-modify the fabric defects. Finally, it is remarkable to highlight that almost all the papers (except [25]) do not refer to communication with other systems on their main bodies or future directions of them, which means that the integration (horizontal or vertical) in terms of industry 4.0 does not a priority in their design. The authors believe that the interoperability and integration of machine vision and cyber-physical systems should be explored in the textile manufacturing industry to enable reliable autonomous decision-making architectures based on multi-data sources.

V. Conclusion

The state-of-the-art analysis conducted on this paper explored the applied vision-based applications within textile manufacturing and how the fabric industries utilize the machine vision techniques to improve the factory's efficiency while reducing the defects. During our study, textile-based papers were examined to identify the unique and the most common features. As a result, machine vision technology is mainly used for quality-related purposes; however, some advancements promote self-adjustment actions and one-batch production. Yet, the horizontal and vertical integration across the factory is not a design priority in the latest vision-based applications and should be explored by the research community in the following years. Hence, the role of machine vision in garment manufacturing and human observation within factories have been left for the future, where a more profound analysis of the maturity level will be explored.

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